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CASTE, LOCAL NETWORKS AND LUCRATIVE JOBS: EVIDENCE FROM RURAL NEPAL

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Caste, local networks and lucrative jobs: Evidence from rural Nepal[*]

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Abstract: We study how local connections to persons in influential positions affect access to migrant jobs and government employment. In rural Nepal, it would not be surprising if social status strongly influenced the access to attractive labor market opportunities. This is not the case. Although much of the variation in migration can be attributed to wealth, education and social identity, household networks have a separate impact on external employment. Well-connected households are more likely to get government jobs and appear to have favorable access to the manpower agencies and informal loans required to finance migration to the Persian Gulf or Malaysia.

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1. Introduction

In low income countries it is common to seek employment in external labor markets in order to increase expected individual earnings or diversify household income.[1] Although economic conditions at home, and prospects elsewhere, are important drivers of labor migration, social factors also impact on when and to where workers move. This paper examines how household networks in the sending area affect where household members migrate for work, and what kind of jobs they are able to find.

It is well documented that individuals searching for jobs in industrial countries rely on their personal networks to locate and acquire attractive jobs (Granovetter 1995; McEntarfer 2003; Ioannides and Loury 2004).[2] There is also a rapidly growing literature addressing the impact of social networks on labor migration in low or middle income countries (Banerjee 1983; Stark 1991; Winters et al. 2001; Munshi 2003). This literature is primarily concerned with migration chains, i.e. the pulling force of having a network of relatives, friends and acquaintances in a particular destination. Few studies have looked into how specific social connections may influence labor migration, which is the question we address here.

Our data are from a random sample of rural households from three purposively sampled villages in the eastern plains of Nepal. Following Kajisa (2007), we construct a network measure by asking households about their acquaintances in high status local

[1] In variants of the Harris-Todaro model, migration is interpreted as an individual decision. In the ‘’new’ economics of migration’ synthesized by Stark (1991), the economic interests of households enter the frame. Lucas (1997) provides an extensive review of the literature addressing internal migration in developing countries.

[2] The prevalence of network-based labor market entry is higher for low and unskilled jobs and occupations elsewhere in South-Asia – see Munshi and Rosenzweig’s (2006) evidence from Mumbai, India.

positions. Apart from data on household networks, information was collected on household migration history, assets, social identity (caste or ethnic), education, demography, shocks and more. We use this data-set to examine how household characteristics, especially how well connected households are, impact on migration outcomes.

Identifying the causal impact of household networks on labor migration is complicated by the fact that observed variation in networks is likely to be endogenously related to the migration outcome. Reverse causality is one concern; migration may enable households to establish new contacts or prevent maintenance of an existing network at the source end. In addition, unobserved household characteristics may influence both household connections and the propensity to migrate. We use an instrumental variable technique to attain exogenous variation in the network variable, which is then used to estimate the causal impact of social connections on migration.

In rural Nepal, it would not be surprising if social status, captured by a household's caste but also by wealth or education, strongly influenced or perhaps even exclusively determined the access to attractive labor market opportunities. This is not the case. Although much of the variation in migration can be attributed to wealth, education and social identity, household networks have a separate impact on external employment, even after these local markers of social status and resources are controlled for. We also find that the caste composition of the village neighbourhood affects migration patterns. Our results may be summarised as mixed: The bad news is that entry to lucrative labor markets from rural Nepal is exclusive, the good news that such exclusion is not only based on traditional markers of status such as caste, education or wealth.

The paper is organized as follows. Section 2 relates our paper to the existing literature on social networks and migration and develops a theoretical backdrop for our empirical analysis. Section 3 presents the data with descriptive statistics. Section 4 presents the potentially endogenous social network measure and describes our identification strategy. Section 5 presents our main results while section 6 concludes.

2. Related literature and hypotheses

Social networks do not feature in classical economics models of labor migration. Yet, having connections, friends and acquaintances in a particular destination may make it more attractive – both financially and socially - for an individual to migrate to the same area. A destination network can provide information about job openings, or temporary resources that newcomers need (Carrington et al. 1996). Destination employers may, in order to reduce asymmetric information and incentive problems, use existing staff to recruit new workers (e.g. Munshi 2003; Iversen et al. 2009). Destination connections may also make migration less socially distressing.

Several studies find evidence that individuals with connections in a potential destination are more inclined to migrate to the same area. Fafchamps and Shilpi (2009) study the determinants of migration destination in Nepal and find that social proximity is a good predictor of destination choice. Banerjee (1983) reports detailed evidence of chain migration among migrants in Delhi. Winters et al. (2001) study how historical and current migration networks affect migration to the United States from different “ejidos” (villages) in Mexico. Over time and within high migration communities, village and family migration networks substitute for each other and cumulative information about migration opportunities becomes a local public good.

In an influential study, Munshi (2003) uses a panel data set of migrants from Mexico to the US to identify the causes and consequences of having a destination network of migrants. He finds that networks improve the outcome (wage) for newcomers and that veteran migrants are particularly valuable for new arrivals. This literature also sheds some light on the underlying mechanisms; i.e. why prior migration breeds new migration (Massey 1987). Munshi suggests that senior migrants act as 'referees' for new arrivals, thus alleviating asymmetric information problems confronting destination employers.[3]

While research on migration networks is plentiful, less is known about how social networks at the source may affect migration, which is the question we address in this paper. In the study closest to ours, Kajisa (2007) measures a personal network as the number of influential individuals a person knows, and the person's proximity to this contact.[4] Using data from a village in the vicinity of Manila, Kajisa finds personal networks to impact on occupational choice. The contacts which affect whether persons end up as employees in small firms are different from those that affect the probability of self-employment.[5] Network effects are also more pronounced for unskilled jobs in small enterprises. Kajisa's (2007) approach adds new insights into how personal networks may facilitate entry into different types of non-farm employment.

We use a similar network measure but focus on a slightly different outcome variable. While Kajisa examined how social networks affect local non-farm employment, we study the impact of local social networks on migration and specifically the access to government jobs and attractive foreign employment.

In South-Asia, government jobs are highly valued and perceived as 'secure, well-paid and prestigious (Jeffrey et al. 2007)' and as avenues for collecting bribes that in addition may ensure subsidized or free access to health services (ibid.). In our study area, well paid jobs in

[3] Iversen et al. (2009) study migration in India and implement an alternative strategy to identify referral effects.

[4] Known as the position generator method in sociology (Lin 2001).

[5] Like Munshi (2003), Kajisa (2007) uses an IV approach to control for network endogeneity.

the Persian Gulf or Malaysia are other coveted options.[6] Young male migrants to these destinations often spend 2-5 years abroad and save up and remit considerable sums of money. A registered manpower agency is the usual intermediary between a destination employer, say in Qatar, and a prospective migrant. A migrant passing the initial selection hurdle will have to pay the manpower agency around 100 000 Nepalese Rupees (appr. 1500 USD). According to our respondents, this fee is usually funded by loans from friends and neighbors.

In spite of credit rationing[7], there still appears to be an excess supply of prospective migrants[8]. The manpower agencies, by screening applicants and organizing interviews, are responsible for and may manipulate selection in a number of ways. Bista (1991) describes Nepali society as permeated by patron-client relations, where any favor, including access to a lucrative foreign job, needs to be reciprocated[9]. If correct, we expect labor migrants to the Gulf and Malaysia to be better connected than others on average.

Another conjecture is that for the type of networks we study, household and village networks are unlikely to be close substitutes. A key finding in Winters et al. (2001) is that in high migration communities, village networks provide services to migrants that in effect become local public goods. One such service is valuable information about job openings or

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[6] For both government and migrant jobs in the Gulf or Malaysia, evidence from elsewhere in the region suggest that such jobs may also be associated with sizeable marriage market premia (e.g. Kodoth 2008).

[7] For more details on credit rationing in the local credit markets in Nepal see Hatlebakk (2009).

[8] An efficiency wage argument may explain why foreign companies may prefer a wage and fee structure that leads to excess supply.

[9] It is hard to agree with all of Bista's claims, but his description of group behavior and nepotism, "aphno mancche" (our people), is still to the point.

more general information about the destination area. In our case and in contrast to what Winters et al. (2001) find, we expect local connections to provide private services that give household members an edge over others in the often fierce competition for coveted government and migrant jobs.

3. Data and descriptive statistics

Although Nepal has a long history of labor migration (see e.g. Gurung 2008), large scale labor migration from Nepal to the Persian Gulf and Malaysia is a recent phenomenon. Between 1995 and 2003, remittances more than doubled most of this rise is attributable to transfers from migrants in these third countries (not Nepal and India) (CBS 2005). The share of remittances from third countries increased from 22.4% in 1995 to 53.3% in 2003 (CBS 2004). Migration to Malaysia and the Persian Gulf has continued to rise and has significantly reduced rural poverty in Nepal (Lokshin et al. 2007).

Located in the eastern plains (terai), Jhapa is one of the main sending districts. Numerous official manpower agencies have offices in the towns of Jhapa and thousands of migrants are sent abroad every month. Jhapa is also an important migration destination because of the gradual migration and settlement of people from the hills in the plains[10]. The original population of the plains has also, over generations, migrated back and forth between Nepal and India. These migration patterns explain the relatively complex caste composition of

[10] This migration from the hills to the plains and the political and economic consequences for terai and Nepal as a whole is described in more detail in Gaige (1975). The plain areas were opened up in the 1950s following an extensive malaria eradication and forest clearing program. The terai's share of Nepal's population increased from 35% in 1953 to 52% in 1991 (Gurung 2001). And Jhapa district, in particular, now has a majority of hill origin people.

villages in Jhapa, where large communities of hill origin indigenous groups and upper castes often co-reside with the indigenous population of the plains.

We selected three rural VDCs of Jhapa district[11]. One is located near the district headquarter of Chandragadhi, another near the main East-West highway and the main border crossing to West-Bengal at Khakarbhitta, with the third located close to a remote part of the border to Kishanganj district in the north-east corner of Bihar (India). In October-November 2008 we randomly selected and interviewed 567 households in these three VDCs of Jhapa district, 81 households in the smallest (and remote) VDC and 243 in each of the two others (which is approximately according to population size). There are 2,579 individuals aged 14 and above in these households. Their main occupations during the last 12 months are reported in Table 1.

Table 1. Present main occupations by location, full adult sample

	Location:							
Occupation:	VDC	Jhapa	Nepal	India	Middle-East	Malaysia	Other	Sum
Farmer	895	0	2	0	0	0	0	897
Self employed	98	39	15	2	0	0	0	154
Worker:								
Farm	402	1	0	12	0	1	0	416
Factory	10	18	6	47	29	19	1	130
Brick industry	0	0	0	0	1	0	0	1
Construction	21	24	5	7	34	3	0	94
Employee-low:								
Restaurant/hotel	0	0	1	18	8	1	0	28
Shop	2	3	3	2	4	2	0	16
Security	1	0	0	7	10	5	0	23
Employee-high:								
Government	11	26	28	4	0	0	0	69
Private office	6	9	9	5	9	0	0	38
Private other	18	11	8	11	20	1	0	69
Other	4	2	2	2	0	0	0	10
Student	219	158	24	11	0	0	2	414
No work	199	7	10	3	0	0	0	219
Not specified					1			1
Sum	1886	298	113	131	116	32	3	2579

[11] VDC (Village Development Committee) is a local administrative unit that is divided into nine wards.

Most government jobs are in the security forces as police or military personnel. As Table 1 shows government employment often implies migration, since a large fraction of household members in government jobs work outside Jhapa districts. Among the 567 households surveyed, 282 individuals had their main occupation outside the country. Excluding migrants who do not work, we are left with 266 migrants. The occupational profiles of these migrants are presented in Table 2, which gives a snapshot of Table 1.

Table 2. Present migrant occupations

	Location:				
Occupation:	India	Middle-East	Malaysia	Other	Sum
Farmer	0	0	0	0	0
Self employed	2	0	0	0	2
<u>Worker:</u>					
Farm	12	0	1	0	13
Factory	47	29	19	1	96
Brick industry	0	1	0	0	1
Construction	7	34	3	0	44
<u>Employee-low:</u>					
Restaurant/hotel	18	8	1	0	27
Shop	2	4	2	0	8
Security	7	10	5	0	22
<u>Employee-high:</u>					
Government	4	0	0	0	4
Private office	5	9	0	0	14
Private other	11	20	1	0	32
Other	2	0	0	0	2
Not specified		1			1
Sum	117	116	32	1	266

Table 2 shows that the most common migrant activity is factory work in India, followed by construction in the Middle-East, and factory work in the Middle-East. In Table 3 we have condensed Table 1 to a smaller number of occupational categories that will be used as outcomes when we regress occupation on social networks and other explanatory variables below.

Table 3. Present main occupation categories

Occupation category:	Full sample	Male	Female
Farmer-Nepal	897	383 (28%)	514 (42%)
Farm-labor-Nepal	403	142 (10%)	261 (21%)
Worker-Nepal	84	73 (5%)	11 (1%)
Employee-low-Nepal	18	13 (1%)	5 (0%)
Self-employed-Nepal	152	93 (7%)	59 (5%)
Private employee-Nepal	61	49 (4%)	12 (1%)
Government employee-Nepal	65	59 (4%)	6 (0%)
Migrant India	117	108 (8%)	9 (1%)
Migrant other country	149	137 (10%)	12 (1%)
Student/No work	633	301 (22%)	332 (27%)
Sum	2579	1358 (100%)	1221 (100%)

The table uncovers a startling gender contrast. Labor force participation is about the same, but women tend to work in agriculture, while men are overrepresented as non-farm labor, private and government employees, and in particular, among migrants. Only 21 migrants are female and most work as domestic servants in the Middle East. With migrants constituting only 2% of the female population, in contrast to 18% of the male population, and given the distinct occupational profiles, we expect the selection process into migration to be different. Given our focus on social networks and migration we will therefore restrict attention to the male sub-sample.

It is of interest to check whether migrants (female migrants included) are clustered in particular households. If we include people who work in Nepal, but outside Jhapa district, the number of migrants increases to 345. An additional 21 people working within Jhapa report themselves to be migrants (two also outside the district as a secondary occupation). This gives a total of 366 migrants. Among these, 331 are in their first migrant job, while 35 have had other migrant jobs. In addition there are 113 previous migrants, adding up to an overall figure of 479 migrants. In Table 4 we report the distribution of these 479 migrants across sample households.

Table 4. Migrants per household

Type of household	No of households	No of migrants
Zero migrants	242	0
Single migrant	212	212
Two migrants	81	162
Three migrants	24	72
Four migrants	7	28
Five migrants	1	5
Total	567	479

In the 113 (20%) households with more than one migrant there are 267 migrants in total. For each of these households we identified the first migrant. If there was more than one person migrating in a given year we chose the oldest as the lead migrant. We have thus defined 154 followers. Table 5 tabulates the destination of these 154 followers against the destination of the first migrant.

Table 5. Followers against first migrant location

	Destination of followers				
First migration:	Jhapa	Nepal	India	Middle-East	Malaysia
Jhapa	2	4	3	6	1
Nepal	1	21	4	8	5
India	1	5	38	11	5
Middle-East	2	6	2	21	2
Malaysia	0	1	0	2	3
N=154	6	37	47	48	16

55% of the followers left for the same destination as the lead migrant, while 32% left for a more distant location, and only 13% for a destination closer to home. In preliminary regressions we included a follower dummy to check whether people are more likely to migrate if other household members have already migrated. As expected the coefficient was positive and significant. Other coefficients in the regression did not change much, suggesting a weak correlation between the follower dummy and other explanatory variables. However, the dummy is most likely endogenous since unobservable household characteristics affect the probability that each household member will migrate. For this reason we did not include the dummy in the regression analyses reported below. Our models are therefore better suited for explaining why a household has migrants as opposed to why a particular household member migrates. In line with this interpretation we also measure social networks and landholdings at the household level.

Explanatory variables

Before embarking on the multivariate analysis, we report descriptive statistics for the key explanatory variables in our analysis; education, landholdings ten years ago, caste/ethnic identity, age and social connections. Tables 6-10 split the main occupation categories for the male sub-sample reported in Table 3 by these explanatory variables.

Education and age

As Table 6 shows, younger men are overrepresented among both migrant groups. Four levels of education feature. In the regression analysis we merge some levels if preliminary analysis suggests no significant difference, for example if people with completed class five have the same probability of finding a migrant job as those with less schooling. There appears to be some non-linearities for education. Men who have completed class five are overrepresented among India migrants, while men who have completed class nine are overrepresented among migrants to third countries. For government jobs, ninth class is the critical level of education, while for private sector the final School Living Certificate (SLC) appears to define a threshold.

Table 6. Present main occupation categories (%) by education and age.

	Education					Age	
Occupation category:	Full sample	SLC	Completed Class 9	Completed Class 5	Less education	14-30	31+
Farmer-Nepal	28	22	26	22	38	13	44
Farm-labor-Nepal	10	0	1	7	24	6	15
Worker-Nepal	5	1	2	9	7	8	3
Employee-low-Nepal	1	1	1	1	1	1	1
Self-employed-Nepal	7	6	6	7	7	5	9
Private employee-Nepal	4	9	3	4	0	4	3
Government employee-Nepal	4	10	8	3	0	3	6
Migrant India	8	4	7	14	6	13	3
Migrant other country	10	16	18	11	2	13	7
Student/No/home work	22	31	28	22	14	35	9
N	1358	275	225	378	460	689	669

Land

The relationship between land and occupation (migration) appears to be linear. For the descriptive statistics we therefore split the sample into four categories of approximately similar number of observations and with cutoffs at 0, 10 and 30 kattha[12]. For landholdings, migration to third countries appears to increase with household land holdings which may reflect that land is used as collateral for loans taken up to cover migration costs.

Table 7. Present main occupation categories (%) by landholdings

	Landholdings			
Occupation category:	Landless	0-10 kattha	10-30 kattha	30+ kattha
Farmer-Nepal	16	22	36	38
Farm-labor-Nepal	29	10	2	0
Worker-Nepal	9	8	4	1
Employee-low-Nepal	1	2	0	1
Self-employed-Nepal	8	10	6	4
Private employee-Nepal	3	3	4	4
Government employee-Nepal	2	2	7	7
Migrant India	12	10	7	3
Migrant other country	3	9	13	15
Student/No work	18	22	22	27
N	353	326	302	377

[12] 20 kattha = 1 bigha = 0.68 hectare.

Ethnic identity

In a country like Nepal we expect social identity to strongly affect occupational choice. Table 8 shows that the patterns observed in our sample substantiate these expectations.

Table 8. Present main occupation categories (%) by ethnic identity

	Caste/ethnic identity						
Occupation category:	Hill B/C	Terai middle	Terai ethnic	Hill ethnic	Muslim	Hill Dalit	Terai Dalit
Farmer-Nepal	36	15	21	31	38	10	0
Farm-labor-Nepal	3	18	21	4	19	15	0
Worker-Nepal	1	2	11	3	0	5	0
Employee-low-Nepal	1	2	1	0	0	0	0
Self-employed-Nepal	4	22	9	4	13	10	0
Private employee-Nepal	4	2	4	4	0	0	50
Government employee-Nepal	6	2	3	6	0	0	0
Migrant India	6	13	8	8	25	30	0
Migrant other country	15	2	5	14	0	5	0
Student/No work	25	24	18	26	6	25	50
N	544	55	507	214	16	20	2

Note: B/C is short for Brahmin/Chettri. Terai and hill refer to the traditional origin of the different groups, with Terai middle castes representing the traditionally dominant groups of the Indian caste system.

The terai middle castes are overrepresented among the self- employed and among India migrants, while the terai ethnic groups, mainly *Rajbansi*, are overrepresented among non-farm manual workers. Muslims and Dalits are overrepresented among India migrants, while the hill origin population is overrepresented among migrants to third countries. It would seem, therefore, that caste and ethnicity crucially affect occupational choice, including migration. Such identity effects may operate via social networks but could also reflect underlying differences in education and wealth. Our multivariate analysis will uncover that our measure of social networks has a direct effect separate from caste, while caste identity has an independent effect also after wealth and education are controlled for.

Notice the small sample sizes for the last three categories in table 8. Since Muslims in Nepal have low social status, we merge the last three categories into one in the regression analysis below. Furthermore, the hill Brahmin/Chettris and the hill ethnic groups, who are all relatively recent in-migrants to the study area, display very similar behavioral patterns; hence, we merge these two categories. This leaves a total of four social groups for our regression analysis keeping the two terai categories apart. In the regression analysis we also include the caste composition of each ward (there are nine wards in each VDC) as explanatory variables[13]. In the regression analysis we prefer to use local terminology and rename the terai middle castes as Madhesi and the terai ethnic groups as Adhivasi.

Social networks

A key question is whether social networks affect the occupational outcome of household members. Using a variant of the position generator method, which is popular in the sociological literature (e.g. Lin 2001) and applied by Kajisa (2007), we asked respondent households about their connections to individuals in positions associated with local status and influence (government officials, politicians, managers of NGOs, large local employers (in particular tea estates), lawyers, police officers and teachers) in the village and within the district three years ago. Some migration events predate this cut-off, but to minimize recall problems we decided to focus on contacts three years ago.

We constructed a social network index from the contacts a household reports to have. To avoid problems associated with reversed causality, an issue taken up below, the index

[13] As the ward-level samples are small, and thus are very imprecise measures of ward-level variables, we use population data to classify the caste composition at the ward level. This introduces another bias. In the survey the enumerators had the option of asking the respondents when they were in doubt about their caste or ethnic group, while the population data is classified (by the same enumerators) based on the names only. From eye-balling the data it appears that this bias is much smaller than the sample bias. For most households there is no doubt about their ethnicity, if your last name is Rajbansi, then you belong to the Rajbansi ethnic group.

excludes contacts that households are likely to have *because* of migration, that is, manpower agencies, credit institutions and other migrants. This leaves a total of 12 possible contacts. The index represents the proportion of these contacts the household knew three years prior to our survey. In Table 9 we split the sample at five or more such contacts. Preliminary analysis suggests, moreover, that knowing the highest government official of the district, the Chief Development Officer (CDO), matters, so we split the sample along this dimension, too.

Table 9. Present main occupation categories (%) and social networks

	Network		CDO	
Occupation category:	5-12 contacts	0-4 contacts	CDO	not
Farmer-Nepal	32	24	36	27
Farm-labor-Nepal	7	15	2	12
Worker-Nepal	4	7	1	6
Employee-low-Nepal	1	1	1	1
Self-employed-Nepal	7	7	6	7
Private employee-Nepal	4	3	4	4
Government employee-Nepal	7	1	11	3
Migrant India	5	12	2	9
Migrant other country	10	11	12	10
Student/No work	25	19	26	22
N	739	619	176	1182

It is evident that households with many contacts are more likely to have members in government jobs, while households with fewer contacts are more likely to have labor migrants in India or farm workers at home. These patterns may not survive multivariate scrutiny since farm workers are also poor and less educated.

Regression results

Our main goal is to estimate the causal impact of local connections on migration and occupational choice. Before addressing the endogeneity of our network variable, we run a simple multinominal regression model with occupation - divided into the categories reported in Table 3 - as dependent variable. With no attempt to address endogeneity, the relation between social networks and occupational choice must be interpreted as a correlation rather than a causal explanation for occupational outcome.

Table 10: Multinomial-Logit regression

Dependent variable: Individual occupations vs. farming									
N = 1338	Farm labor	Labor	Empl. low	Self-empl.	Priv. empl.	Gov. empl.	India migr.	Other migr.	No occup.
Network	-3.795***	-2.906***	-0.177	-0.073	-0.070	1.554*	-3.243***	-2.605***	0.861
	(0.949)	(1.122)	(1.734)	(0.739)	(0.936)	(0.799)	(0.954)	(0.774)	(0.680)
Age	0.152***	0.159*	0.169	0.085	0.002	0.257***	0.216**	0.331***	-0.719***
	(0.052)	(0.081)	(0.150)	(0.055)	(0.079)	(0.096)	(0.097)	(0.087)	(0.048)
Age-sq	-0.002***	-0.003***	-0.003	-0.001**	-0.001	-0.004***	-0.005***	-0.006***	0.008***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Land	-0.161***	-0.042***	-0.001	-0.012***	-0.006	-0.006*	-0.026***	0.001	-0.001
	(0.031)	(0.013)	(0.007)	(0.004)	(0.004)	(0.004)	(0.008)	(0.003)	(0.003)
Class	-2.120***	-1.058**	-0.216	0.460	1.152***	1.582***	-0.296	0.519**	1.536***
nine+	(0.747)	(0.456)	(0.709)	(0.305)	(0.382)	(0.399)	(0.304)	(0.256)	(0.283)
Hill origin	-1.240***	-1.566***	-0.687	-1.389***	-0.589	-0.325	-0.281	0.545*	-0.292
	(0.303)	(0.370)	(0.648)	(0.289)	(0.370)	(0.389)	(0.284)	(0.295)	(0.264)
Musl/Dalit	1.065	-0.716	2.903	1.542	-2.478	-6.015	2.991**	-2.937	1.761
share	(1.372)	(1.823)	(2.647)	(1.556)	(4.359)	(4.328)	(1.445)	(2.756)	(1.664)
Madhesi	2.153	0.366	1.939	6.052**	5.520	-5.706	6.661**	1.128	2.189
Share	(2.646)	(3.285)	(6.510)	(2.666)	(3.568)	(4.062)	(2.715)	(2.820)	(2.604)
Adhivasi	0.420	-1.053	0.854	0.176	0.111	0.370	0.629	-0.359	0.935
Share	(0.823)	(0.964)	(2.001)	(0.868)	(1.121)	(1.001)	(0.865)	(0.796)	(0.755)
_cons	-0.486	0.595	-5.301*	-1.841*	-1.054	-6.475***	-0.878	-3.856***	10.936***
	(1.061)	(1.371)	(2.877)	(1.104)	(1.414)	(1.774)	(1.435)	(1.407)	(0.824)

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Pseudo R2 = 0.3109.

When we control for household caste, education and landholdings and for the caste composition of the ward where a household is resident, migrant households tend to have weaker social networks than others. Notice also that households resident in wards (neighborhoods) with a high concentration of terai middle castes (Madhesis), ceteris paribus, are more likely to be self employed outside agriculture and to be migrants to India. The latter also applies to households in Muslim or Dalit wards. For own caste/ethnic identity households of hill origin, themselves in-migrants and settlers in the study villages in Jhapa, are more likely to have members working in Malaysia or the Persian Gulf. Other control variables have the expected signs, households with land do agriculture, while those with education (completed class nine or more) are employed in private and government sector or migrate to third countries. Except for the expected finding that laborers do not have extensive contact with powerful local people, it is noteworthy that migrants have fewer such contacts, while government employees have more. We have also estimated probit models for each of the two migration outcomes (India and Malaysia and the Persian Gulf) and for government jobs. The results are reported below in Tables 12-14. The patterns in the multinomial logit model are preserved in the probit models; households who send members to work in India or the Persian Gulf have fewer connections than others.

It is perhaps surprising that households with migrants in Malaysia or the Persian Gulf have relatively few connections. If these jobs are lucrative one would expect a queue of applicants waiting to get an offer and that those who come from a well connected household would get easier access. This argument overlooks that work migration to a far away destination, for example to Qatar, is the outcome of a two stage process. First, a household must be willing to send a member to a distant destination. Second if a household perceives this as an attractive option, it must be able to find a job in Qatar. How well connected a household is may affect both stages in this process, and possibly in opposite directions. Well connected households may hesitate to send a household head to Qatar since this makes it harder to maintain its connections at home. On the other hand, the probability that households aiming to send a member to Qatar, will find an opening is probably improved if the household is well connected. A priori we do not know which of these effects that dominates. A causal understanding of the results reported above suggests that the first effect dominates. But, as noted above, a causal interpretation is as yet premature.

4 Identifying the causal impact of social networks on occupation

Instruments

The strength of a household's social network is not an exogenous variable. Reverse causality is one concern; migration may enable a household to establish new contacts or prevent it from maintaining old ones. Indeed, the negative association between social networks and migration to Malaysia and the Gulf could reflect that having breadwinners at far away destinations makes it difficult to create and sustain connections at the village end. We attempt to minimize this problem by (i) constructing a social network index that excludes the connections most likely to have been established during the migration process and (ii) by asking households about their connections three years ago. Another potential source of endogeneity is that unobserved household characteristics may influence capacity and willingness to develop connections as well as the propensity to send members to Malaysia and the Persian Gulf.

To address these two concerns we need instrumental variables that generate exogenous variation in household connections and use two variables to instrument for social networks. The first is an indicator (*bornhere*) of whether or not the household head was born in the household's current village of residence. Households that recently arrived in our study villages are likely to have networks also in the area where they came from. This suggests that households with a head not born in the village are more likely to have a larger set of connections to individuals in influential positions in the region, which in turn makes it more likely that they will migrate for work. Our data show that households who recently have arrived in the village (*bornhere* = 0) have almost 15% more contacts on average than households with a household head born in the village.

A second potential instrument variable exploits the fact that we have data from three villages which differ in remoteness (measured as distance to the district headquarters). Distance to the district headquarter is likely to affect households' opportunities for developing connections to individuals holding prominent positions in politics, business and civil society. Table 11 indicates that this is indeed the case.

Table 11. Social contacts 3 years ago, frequency.

	VDC 1	VDC 2	VDC 3
Estimated time by bicycle to district headquarter	60 min	30 min	180 min
Number of contacts			
1	1	1	5
2	4	3	3
3	16	14	21
4	29	20	29
5	22	30	21
6	11	10	13
7	7	6	4
8	3	4	1
9	4	2	0
10	1	2	4
11	1	4	0
12	1	5	0
N	569	605	184

The median number of contacts is four in the two more remote VDCs and five in the centrally located VDC 2. The mean is 4.3 in the most remote VDC 3, 4.9 in VDC 1 and 5.5 in the centrally located VDC 2. Households in the centrally located VDC are thus slightly better connected than individuals in the more remote villages.

A potential problem with using village dummies as instruments is that distance from headquarter may not only affect occupational outcomes via network connections. It is perceivable that the remoteness of a village has a direct effect on the local labor market and therefore on people's propensity to migrate for work. This point may be valid for India migration, but turns out to be less of a concern when we estimate the impact of connections on migration to Malaysia and the Persian Gulf. Firstly, we suggest that local variations in the labor market are unlikely to affect the radical and far-reaching decision of sending a household member to Malaysia or the Persian Gulf. Hence to the extent that distance from the district headquarter affects the fraction of households sending migrants to a destination like Qatar, this effect is likely to operate via differences in the networks that households have access to. Our results (discussed further below) support this conjecture. When VDC dummies are included in our probit model, residence in the remote village has a significantly negative impact on the likelihood of having a household member in government jobs or as migrants in Malaysia and the Persian Gulf. If unobserved local labor market conditions were pushing people to migrate to Malaysia or the Gulf, the sign of the remote VDC dummy should be positive. When we use the *bornhere* dummy to instrument for social network, all village dummies turn insignificant. This pattern indicates (i) that migration varies between villages and (ii) that this variation is driven by between village heterogeneity in the strength of the social networks.

Our results suggest that a similar reasoning extends to government jobs. We do not expect households that moved to the village during the last generation to be more likely to have government jobs, except for the fact that they may have a better social network. Similarly, we expect household members to take up a government job if they can, independently of the location of their village[14]: A policeman or soldier will have to move regularly between districts throughout his working life. Whether the rest of the household lives near a particular district headquarter, or not, is not likely to affect the decision to enter such a job. Again, our conjecture is supported by the fact that the VDC dummies are both negative in the probit model and turn insignificant when we use the *bornhere* dummy to instrument for social network.

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[14] It is our impression that these jobs in the security forces are still rated as among the most attractive among young men, despite the ongoing conflict in Nepal (it appears that even Maoist soldiers have a long-term target of entering the government forces after the peace process has been completed).

Results

The results from the IV regressions are reported in Table 12 – 14. In the tables we compare IV regressions with a standard – not instrumented – probit model. First we estimate the likelihood of migrating to Malaysia and the Persian Gulf. We start with the *bornhere* dummy as a single instrument. When the village dummies turned out to be non-significant these were added as instruments. For the IV we estimate the linear version as well, again with and without the village dummies. Finally we add ward (sub-village) effects in the linear IV regression, first as random and then as fixed effects.

Table 12. Migration to Malaysia and the Persian Gulf

N=1338	Probit	Probit	IV-Probit	IV-Probit	IV-Reg	IV-Reg	IV-XT-RE	IV-XT-FE
Network3	-1.385***	-1.246**	4.144*	3.964***	0.820	0.809*	0.776**	0.647
	(0.530)	(0.520)	(2.320)	(1.070)	(1.118)	(0.437)	(0.389)	(0.598)
vdc1	-0.072		0.028		-0.001			
	(0.139)		(0.152)		(0.035)			
vdc3	-0.471***		0.034		0.001			
	(0.150)		(0.348)		(0.086)			
Age	0.283***	0.279***	0.168	0.176***	0.007**	0.007***	0.007***	0.007***
	(0.043)	(0.041)	(0.120)	(0.063)	(0.003)	(0.002)	(0.003)	(0.003)
age2	-0.004***	-0.004***	-0.003	-0.003***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Kattha	0.003*	0.003*	-0.007*	-0.006***	-0.001	-0.001*	-0.001*	-0.001
	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
nineplus	0.196*	0.174	-0.265	-0.250*	-0.020	-0.019	-0.017	-0.009
	(0.113)	(0.112)	(0.266)	(0.142)	(0.098)	(0.043)	(0.037)	(0.051)
musl/dalit	-0.726*	-0.678	-0.888*	-0.906*	-0.135	-0.134	-0.145**	-0.152*
	(0.422)	(0.419)	(0.522)	(0.486)	(0.110)	(0.083)	(0.069)	(0.086)
madhesi	-1.019**	-1.072**	-0.377	-0.411	-0.040	-0.040	-0.037	-0.031
	(0.459)	(0.470)	(0.632)	(0.428)	(0.085)	(0.050)	(0.056)	(0.065)
adhivasi	-0.617***	-0.612***	-0.213	-0.235	-0.056	-0.056*	-0.056**	-0.059*
	(0.220)	(0.213)	(0.319)	(0.177)	(0.052)	(0.031)	(0.025)	(0.031)
musl/dalit%	-2.549**	-2.289**	-1.718	-1.668	-0.146	-0.148	-0.108	
	(1.023)	(0.958)	(1.210)	(1.027)	(0.129)	(0.120)	(0.135)	Ward
Madhesi%	-1.605	-0.936	-1.761	-1.804	-0.407	-0.404	-0.414	fixed
	(1.492)	(1.586)	(1.196)	(1.218)	(0.325)	(0.270)	(0.274)	effects
Adhivasi%	-0.122	-0.304	-1.040**	-0.999***	-0.242	-0.241***	-0.211**	
	(0.398)	(0.350)	(0.443)	(0.378)	(0.208)	(0.091)	(0.097)	
Constant	-4.313***	-4.377***	-3.975***	-4.051***	-0.129	-0.126	-0.129	-0.187
	(0.553)	(0.553)	(1.294)	(0.763)	(0.297)	(0.121)	(0.111)	(0.200)
Pseudo-R-sq.	0.2206	0.2131						
First stage OLS			network3	network3	network3	network3	network3	network3
bornhere			-0.044	-0.045#	-0.044	-0.044	-0.046***	-0.051***
			(0.032)	(0.028)	(0.032)	(0.032)	(0.015)	(0.015)
vdc1			-0.017	-0.016	-0.017	-0.017	-0.018	
			(0.019)	(0.015)	(0.019)	(0.019)	(0.012)	
vdc3			-0.069***	-0.068***	-0.069***	-0.069***	-0.070***	
			(0.022)	(0.022)	(0.023)	(0.023)	(0.016)	
Age			0.002*	0.002*	0.002	0.002	0.002	0.002
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
age2			-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Kattha			0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
nineplus			0.076***	0.076***	0.076***	0.076***	0.076***	0.076***
			(0.018)	(0.018)	(0.018)	(0.018)	(0.010)	(0.010)
musl/dalit			0.084	0.085	0.084	0.084	0.093***	0.106***
			(0.074)	(0.073)	(0.075)	(0.075)	(0.030)	(0.031)
madhesi			-0.027	-0.027	-0.027	-0.027	-0.028	-0.034
			(0.035)	(0.033)	(0.035)	(0.035)	(0.026)	(0.026)
adhivasi			0.001	0.002	0.001	0.001	0.002	0.004
			(0.030)	(0.027)	(0.030)	(0.030)	(0.016)	(0.016)
musl/dalit%			0.067	0.066	0.067	0.067	0.047	
			(0.115)	(0.111)	(0.115)	(0.115)	(0.067)	Ward
Madhesi%			0.185	0.187	0.185	0.185	0.181	fixed
			(0.127)	(0.130)	(0.128)	(0.128)	(0.123)	effects
Adhivasi%			0.192***	0.192***	0.192***	0.192***	0.182***	
			(0.064)	(0.064)	(0.065)	(0.065)	(0.035)	
Constant			0.258***	0.257***	0.258***	0.258***	0.265***	0.329***
			(0.033)	(0.034)	(0.034)	(0.034)	(0.027)	(0.023)
Athrho			-1.059	-1.005***				
			(0.746)	(0.343)				
R-squared					0.3020	0.3020		

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1, # p<0.11.
FE (and RE) effects are ward effects.

In the IV regressions there is a robust positive causal effect of social networks on the probability of getting a job in Malaysia or Gulf countries, in support of our main hypothesis. Furthermore, we find that village caste composition matters, households resident in a village dominated by terai ethnic groups are less likely to have migrant members. This may be interpreted as another network effect. In addition, social identity matters since the lower status groups of Dalits, Muslims and the terai ethnic groups are less likely to migrate. Furthermore, once we control for the endogenous network variable, other resources, such as education and land, reduce the probability of migration, which is in contrast to the ordinary probit models where the correlations were positive. The change in sign must be driven by positive correlations with the social network variable. These negative effects of resource endowments are plausible since land and education are likely to improve opportunities at home, with lower returns (of education) in the destination where most migrants undertake manual work.

For migration to India (reported in Table 13) the social network has a negative effect in the probit regression with the negative effect amplified in the IV regressions.

Table 13. Migration to India

N=1338	Probit	Probit	IV-Probit	IV-Probit	IV-Reg	IV-Reg	IV-XT-RE	IV-XT-FE
Network3	-1.392***	-1.446***	-4.377#	-4.601***	-0.381	-0.489**	-0.489#	-0.595
	(0.427)	(0.436)	(2.732)	(1.159)	(0.510)	(0.240)	(0.303)	(0.514)
vdc1	0.228**		0.152		0.026			
	(0.098)		(0.125)		(0.017)			
vdc3	0.308***		0.058		0.013			
	(0.115)		(0.321)		(0.038)			
Age	0.197***	0.199***	0.179**	0.177***	-0.002	-0.002	-0.002	-0.002
	(0.062)	(0.063)	(0.081)	(0.062)	(0.002)	(0.002)	(0.002)	(0.002)
age2	-0.004***	-0.004***	-0.003**	-0.003***	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Kattha	-0.009**	-0.009**	-0.002	-0.002	0.000	0.000	0.000	0.001
	(0.003)	(0.004)	(0.008)	(0.004)	(0.001)	(0.000)	(0.001)	(0.001)
Nineplus	-0.355**	-0.361**	-0.064	-0.042	-0.030	-0.022	-0.022	-0.010
	(0.152)	(0.149)	(0.417)	(0.245)	(0.047)	(0.033)	(0.029)	(0.043)
musl/dalit	0.764***	0.685***	0.926***	0.857***	0.176**	0.171**	0.171***	0.189**
	(0.244)	(0.236)	(0.307)	(0.318)	(0.085)	(0.070)	(0.055)	(0.074)
Madhesi	-0.238	-0.225	-0.389	-0.414	-0.032	-0.041	-0.041	-0.061
	(0.284)	(0.274)	(0.309)	(0.285)	(0.061)	(0.055)	(0.046)	(0.056)
Adhivasi	-0.191	-0.218	-0.272	-0.292	-0.031	-0.036	-0.036*	-0.037
	(0.203)	(0.204)	(0.199)	(0.196)	(0.031)	(0.027)	(0.020)	(0.026)
musl/dalit%	0.082	0.507*	0.140	0.320	0.094	0.138**	0.138	
	(0.357)	(0.281)	(0.441)	(0.431)	(0.070)	(0.065)	(0.103)	Ward
Madhesi%	3.248***	2.853*	3.350***	3.280***	0.472*	0.472*	0.472**	fixed
	(1.108)	(1.460)	(1.047)	(1.094)	(0.262)	(0.258)	(0.190)	effects
Adhivasi%	0.130	0.346	0.724	0.879**	0.076	0.113*	0.113	
	(0.365)	(0.389)	(0.732)	(0.378)	(0.121)	(0.068)	(0.073)	
Constant	-3.121***	-3.028***	-1.938	-1.786*	0.277**	0.313***	0.313***	0.407**
	(0.853)	(0.851)	(1.898)	(1.083)	(0.135)	(0.070)	(0.086)	(0.172)
Pseudo-R-sq.	0.2077	0.2026						
First stage OLS			network3	network3	network3	network3	network3	network3
Bornhere			-0.044	-0.043	-0.044	-0.044	-0.044***	-0.051***
			(0.032)	(0.031)	(0.032)	(0.032)	(0.015)	(0.015)
vdc1			-0.017	-0.021	-0.017	-0.017	-0.017*	
			(0.019)	(0.018)	(0.019)	(0.019)	(0.010)	
vdc3			-0.069***	-0.069***	-0.069***	-0.069***	-0.069***	
			(0.022)	(0.022)	(0.023)	(0.023)	(0.014)	
Age			0.002*	0.002*	0.002	0.002	0.002	0.002
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
age2			-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Kattha			0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Nineplus			0.076***	0.076***	0.076***	0.076***	0.076***	0.076***
			(0.018)	(0.018)	(0.018)	(0.018)	(0.010)	(0.010)
musl/dalit			0.084	0.082	0.084	0.084	0.084***	0.106***
			(0.074)	(0.075)	(0.075)	(0.075)	(0.030)	(0.031)
Madhesi			-0.027	-0.028	-0.027	-0.027	-0.027	-0.034
			(0.035)	(0.035)	(0.035)	(0.035)	(0.026)	(0.026)
Adhivasi			0.001	0.000	0.001	0.001	0.001	0.004
			(0.030)	(0.029)	(0.030)	(0.030)	(0.016)	(0.016)
musl/dalit%			0.067	0.072	0.067	0.067	0.067	
			(0.115)	(0.115)	(0.115)	(0.115)	(0.064)	Ward
Madhesi%			0.185	0.183	0.185	0.185	0.185	fixed
			(0.127)	(0.123)	(0.128)	(0.128)	(0.103)	effects
Adhivasi%			0.192***	0.195***	0.192***	0.192***	0.192***	
			(0.064)	(0.064)	(0.065)	(0.065)	(0.030)	
Constant			0.258***	0.259***	0.258***	0.258***	0.258***	0.329***
			(0.033)	(0.033)	(0.034)	(0.034)	(0.026)	(0.023)
Athrho			0.542	0.600**				
			(0.640)	(0.302)				
R-squared					0.3020	0.3020		

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1, # p<0.11.
FE (and RE) effects are ward effects.

The difference between the IV and the ordinary estimates suggests an underlying positive correlation between network and the probability of migration. It is possible that migrants learn the value of having connections while abroad since contacts are important for finding jobs and accommodation in India. However, the causal negative effect appears to dominate even in the probit regressions. The causal effect suggests that households with local connections prefer alternatives to migration to India. Jobs in India are not well paid and Nepalese citizens often feel discriminated against.

As we may expect, households resident in villages with more Madhesis (people of Indian origin) are more likely to send labor migrants to India, and Dalits and Muslims are more likely to work in India. However, once we control for the endogenous network variable, endowments of education and land cease to matter. In the probit analysis, on the other hand, these variables contribute negatively, but these effects are picked up by the network variable in the IV regressions.

In sum our findings suggest that India is an inferior labor market which is plausible since the wage level in India is not much higher than in Nepal for the low status jobs that most people end up in.

The final category we consider is government jobs. The jobs we are looking at here also involve migration since policemen and soldiers are regularly transferred between duty-stations within Nepal. Just as for India migration, Table 14 reveals that the IV estimates amplifies the probit estimates, but this time both effects are positive. There may be an underlying negative reverse causality since people, because of regular job transfers, may not be able to maintain their social contacts. In any case, all parameters for the network variable are positive, which supports the hypothesis that contacts affect the prospects for getting attractive government jobs. Furthermore, and not surprising, our data indicate that Dalits and Muslims are excluded from getting government jobs; we also find that people who live in

Madhesi villages are less likely to get jobs in the security forces, as indicated in the news media after the 2007 Madhesi upraising[15]. Land also has a negative effect indicating that joining the security forces is an alternative for households where land holdings are too marginal to be split among all brothers.

[15] For more information on the Madhesi ethnic conflict see Hatlebakk (2007).

Table 14. Government jobs

N=1338	Probit	Probit	IV-Probit	IV-Probit	IV-Reg	IV-Reg	IV-XT-RE	IV-XT-FE
network3	1.129***	1.270***	4.644	5.555***	0.336	0.621**	0.585**	0.183
	(0.370)	(0.353)	(3.283)	(0.964)	(0.500)	(0.242)	(0.257)	(0.408)
vdc1	-0.257*		-0.131		-0.022#			
	(0.152)		(0.204)		(0.014)			
vdc3	-0.514**		-0.171		-0.025			
	(0.208)		(0.466)		(0.034)			
Age	0.186***	0.182***	0.145	0.114**	0.006***	0.006***	0.006***	0.007***
	(0.044)	(0.044)	(0.093)	(0.050)	(0.002)	(0.002)	(0.002)	(0.002)
age2	-0.002***	-0.002***	-0.002*	-0.002**	-0.000***	-0.000***	-0.000***	-0.000***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Kattha	-0.002*	-0.002	-0.008	-0.009***	-0.001	-0.001**	-0.001**	-0.000
	(0.001)	(0.001)	(0.005)	(0.002)	(0.001)	(0.000)	(0.000)	(0.001)
Nineplus	0.747***	0.727***	0.334	0.141	0.051	0.030	0.033	0.062*
	(0.162)	(0.153)	(0.607)	(0.231)	(0.042)	(0.019)	(0.024)	(0.033)
Madhesi	0.330	0.327	0.513	0.537	0.030	0.049	0.048	0.017
	(0.447)	(0.459)	(0.413)	(0.338)	(0.041)	(0.033)	(0.037)	(0.044)
Adhivasi	-0.020	-0.004	0.137	0.189	0.002	0.013	0.013	-0.002
	(0.171)	(0.171)	(0.238)	(0.182)	(0.022)	(0.019)	(0.017)	(0.022)
musl/dalit%	-1.664	-2.655*	-1.850	-2.173*	-0.040	-0.091	-0.076	
	(1.752)	(1.598)	(1.567)	(1.261)	(0.063)	(0.067)	(0.077)	Ward
madhesi%	-4.075**	-3.670**	-3.963**	-3.521***	-0.329**	-0.361***	-0.339**	fixed
	(1.788)	(1.548)	(1.807)	(1.354)	(0.157)	(0.139)	(0.167)	effects
adhivasi%	0.319	0.151	-0.506	-0.798*	-0.015	-0.083	-0.072	
	(0.380)	(0.438)	(0.939)	(0.455)	(0.107)	(0.069)	(0.063)	
Constant	-5.543***	-5.615***	-5.463***	-4.899***	-0.180	-0.259***	-0.253***	-0.166
	(0.765)	(0.756)	(1.505)	(0.996)	(0.129)	(0.066)	(0.072)	(0.138)
Pseudo-R-sq.	0.2117	0.2006						
First stage OLS			network3	network3	network3	network3	network3	network3
Bornhere			-0.041	-0.038	-0.041	-0.041	-0.042***	-0.047***
			(0.034)	(0.033)	(0.034)	(0.034)	(0.015)	(0.015)
vdc1			-0.021	-0.023	-0.021	-0.021	-0.022*	
			(0.018)	(0.016)	(0.018)	(0.018)	(0.011)	
vdc3			-0.067***	-0.068***	-0.067***	-0.067***	-0.068***	
			(0.022)	(0.022)	(0.022)	(0.022)	(0.015)	
Age			0.002*	0.002*	0.002*	0.002*	0.002*	0.002
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
age2			-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Kattha			0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Nineplus			0.074***	0.074***	0.074***	0.074***	0.074***	0.073***
			(0.019)	(0.019)	(0.019)	(0.019)	(0.010)	(0.010)
Madhesi			-0.037	-0.038	-0.037	-0.037	-0.038	-0.046*
			(0.036)	(0.036)	(0.036)	(0.036)	(0.026)	(0.026)
Adhivasi			-0.007	-0.009	-0.007	-0.007	-0.007	-0.005
			(0.033)	(0.032)	(0.033)	(0.033)	(0.016)	(0.016)
musl/dalit%			0.142*	0.142*	0.142*	0.142*	0.135**	
			(0.077)	(0.076)	(0.077)	(0.077)	(0.060)	Ward
madhesi%			0.179	0.176	0.179	0.179	0.175	fixed
			(0.126)	(0.124)	(0.126)	(0.126)	(0.116)	effects
adhivasi%			0.205***	0.206***	0.205***	0.205***	0.199***	
			(0.060)	(0.059)	(0.060)	(0.060)	(0.033)	
Constant			0.256***	0.257***	0.256***	0.256***	0.261***	0.335***
			(0.032)	(0.032)	(0.032)	(0.032)	(0.026)	(0.023)
Athrho			-0.668	-0.978**				
			(0.876)	(0.386)				
R-squared					0.2978	0.2978		

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1, # p<0.11.
FE (and RE) effects are ward effects.

Are connections a private or a public good?

Winters et al. (2001) find that in high migration communities village networks become local public goods. It is interesting to check if this is the case also in our data. We focus on a different network than Winters et al. (2001) since they focus on networks of migrants while we study connections to powerful persons in the sending area. Apriori one would expect that the kind of network we measure first and foremost is a private good. Our results indicate that this is indeed the case. In robustness checks we find that the measure of the private (household level) social network is significant (in the ordinary probit regressions) also when we add the mean of the social network at the VDC level. It appears that this mean measures the same as the VDC dummies in the first regression reported in tables 12-14. This suggests that the VDC dummies pick up network effects at the VDC level, which supports our hypothesis of VDC dummies as good instruments for the social network variable.[16] As the coefficient for the private social network does not change much when the VDC level network is controlled for, we suggest that there is a clear private good element of the local social network as a resource that is vital for securing coveted migrant jobs.

6. Conclusions

Household social networks improve the odds that Nepali men will get lucrative migrant jobs in Malaysia and the Persian Gulf, or attractive government jobs within Nepal. This is so even when we control for sub-village caste and ethnic composition and for the household's own caste or ethnic identity along with indicators of education and household wealth. It appears that distance to the district headquarter matters for the strength of the social network, but we

[16] Note that we cannot add VDC-level variables in the IV-regressions as VDC is used as an instrument for the household level social networks.

do not expect this local variation in distance to have a direct effect on the probability of getting external jobs, any effect will be via social connections. We therefore use village dummies as instruments for the social network variable. Based on previous work in the region (Hatlebakk 2009), we know that social connections are important for getting loans in the informal credit market, and access to credit is one of the barriers to foreign migration reported by our respondents. Well connected people may also have easier access to government jobs as well as the manpower agencies that select candidates for migration to the Gulf and Malaysia.

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